# PROJECT REPORT
# <u>RECASEA</u>

Topic: **Reliable Energy Consumption Analysis System for Energy-Efficient Appliances**

Team ID : **Team-592406**
Team Size : 4

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# INTRODUCTION

## Project Overview

Recasea, a comprehensive energy consumption analysis system, revolutionizes the evaluation of power usage for energy-efficient appliances. Through intricate machine learning algorithms and large volumes of historical data, it forecasts power consumption trends, meticulously examines appliance usage behavior, and furnishes tailored insights. By allowing users to input appliance specifications and time parameters, Recasea predicts energy usage, benchmarks it against established norms, and delivers invaluable assessments. The project integrates predictive models, data analytics, and user-friendly interfaces to empower both individuals and businesses in optimizing energy usage. Its multi-dimensional approach facilitates comprehensive analysis, aiding in forecasting future consumption trends and recommending strategies for sustainable energy practices.

## Purpose

The primary aim of Recasea is to promote sustainable energy practices by offering personalized insights and actionable recommendations. It seeks to empower users with the ability to make informed decisions regarding appliance usage, thereby reducing energy consumption. By leveraging historical data and advanced algorithms, the project aims to instill a culture of energy efficiency, encouraging users to embrace eco-friendly behaviors. Recasea is dedicated to fostering an understanding of power usage patterns, providing valuable insights, and ultimately contributing to the larger goal of a greener and more sustainable future.

# LITERATURE SURVEY

**Existing Problem**
The proliferation of building energy consumption data has sparked an upsurge in data-driven methods for energy analysis across various architectural models. These approaches encompass predictive models such as artificial neural networks and statistical regression, addressing needs like load forecasting and energy mapping. However, their adaptability to individual buildings and user preferences remains a challenge. Current models lack granularity in accommodating micro-level alterations and aligning with users' distinct energy usage patterns, hindering precise energy predictions. Moreover, integrating renewable energy sources into these frameworks presents complexities. As urban centers aim for sustainable growth, refining these data-driven models is crucial to optimize individual building retrofits, address unavailable variables, and align predictions with user preferences. This evolution is essential to foster energy-conscious decisions and cater to specific consumption behaviors, reducing over-usage, cutting electricity bills, and facilitating eco-friendly choices daily.

**Problem Statement Definition**
This study addresses limitations in prevalent data-driven building energy analysis by refining models for precise adaptations to individual buildings and user preferences. The need arises from the imperative to curb over-usage, minimize electricity bills, and promote environmentally conscious choices daily. The existing gap hampers these objectives, with data-driven models lacking adaptability to specific user behaviors and intricate energy consumption patterns. By enhancing these models to accommodate micro-level changes, integrate renewable sources, and align with user preferences, the research aims to enable more accurate predictions and conscious energy choices. This refined approach seeks to contribute to the reduction of over-usage, cost savings on electricity bills, and fostering environmentally conscious decisions, thereby ensuring a sustainable and energy-efficient future.

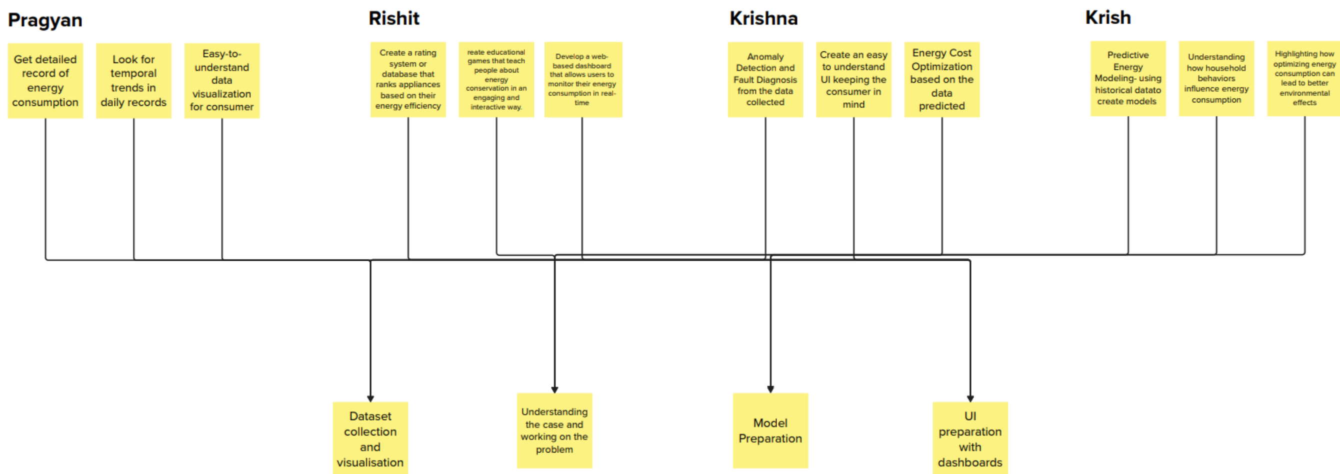
**References**:

https://www.sciencedirect.com/science/article/pii/S136403211731362X
https://ieeexplore.ieee.org/abstract/document/6822319
https://www.sciencedirect.com/science/article/pii/S0140988318301440

# IDEATION AND PROPOSED SOLUTION

## Empathy Map

# Brainstorm Map



# REQUIREMENT ANALYSIS

**Functional Requirements**

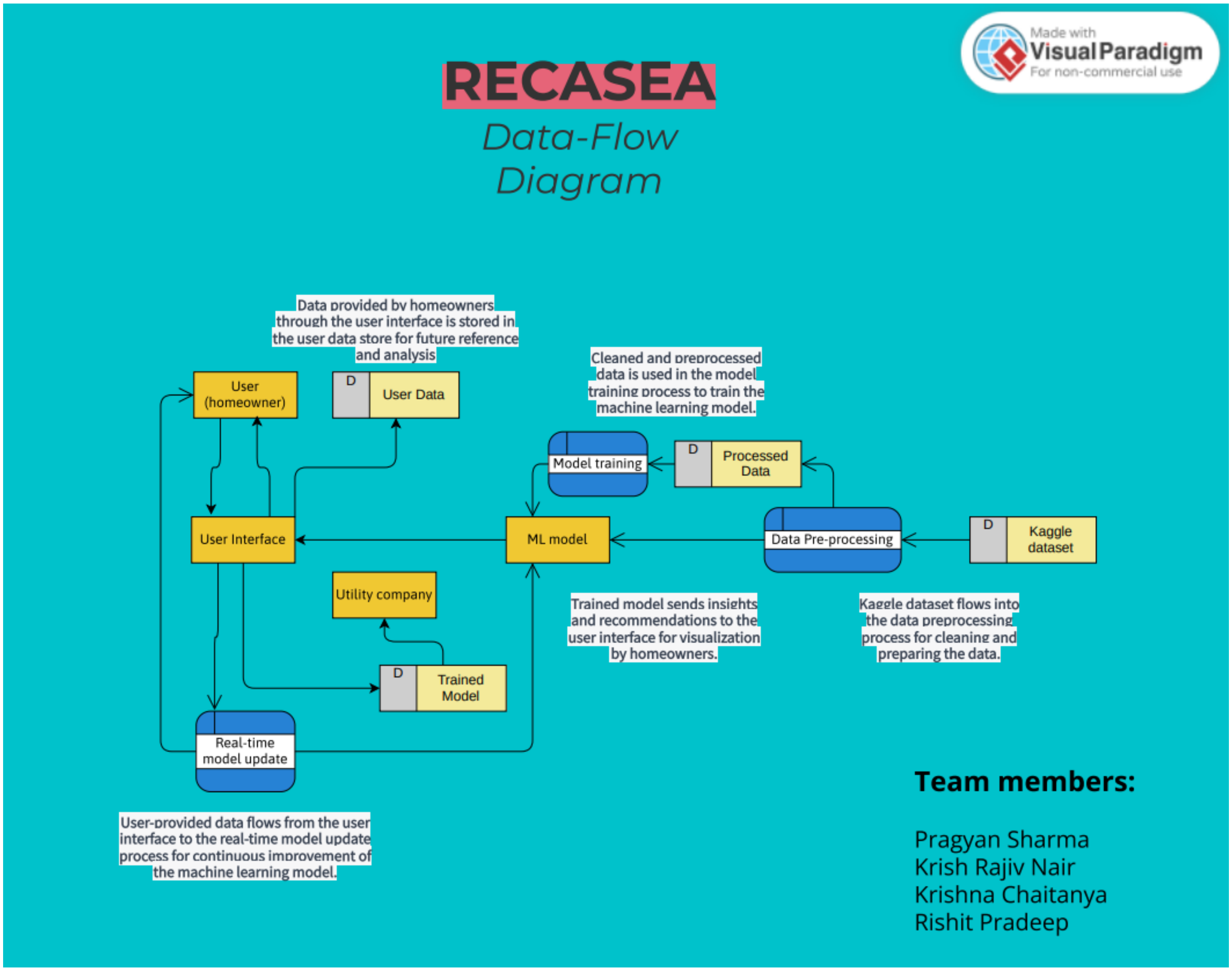
1. Prediction Capability: Provide accurate forecasting of energy usage based on input parameters such as appliance consumption, time of day, and day type (weekday/weekend).
2. Comparative Analysis: Enable comparison between predicted and normal energy usage for insightful assessments.
3. Recommendation System: Generate energy conservation suggestions personalized to users, encouraging energy-efficient practices.
4. Usability: Offer an intuitive interface for effortless data input and user-friendly interpretation of results.
5. Data Handling: Efficiently process and manage diverse data sets for robust predictions.

**Non-Functional Requirements**

1. Accuracy: Ensure high precision in energy usage predictions for reliable insights and recommendations.
2. Security: Implement robust data security measures to protect user information and comply with privacy regulations.
3. Scalability: Design the system to accommodate future expansions and varying data sources for scalability.
4. Performance: Ensure efficient performance, delivering timely predictions and recommendations without significant delays.
5. Compliance: Adhere to industry standards and regulatory requirements related to energy usage data analysis.
6. Reliability: Maintain system uptime and reliability for consistent access and usage by users.

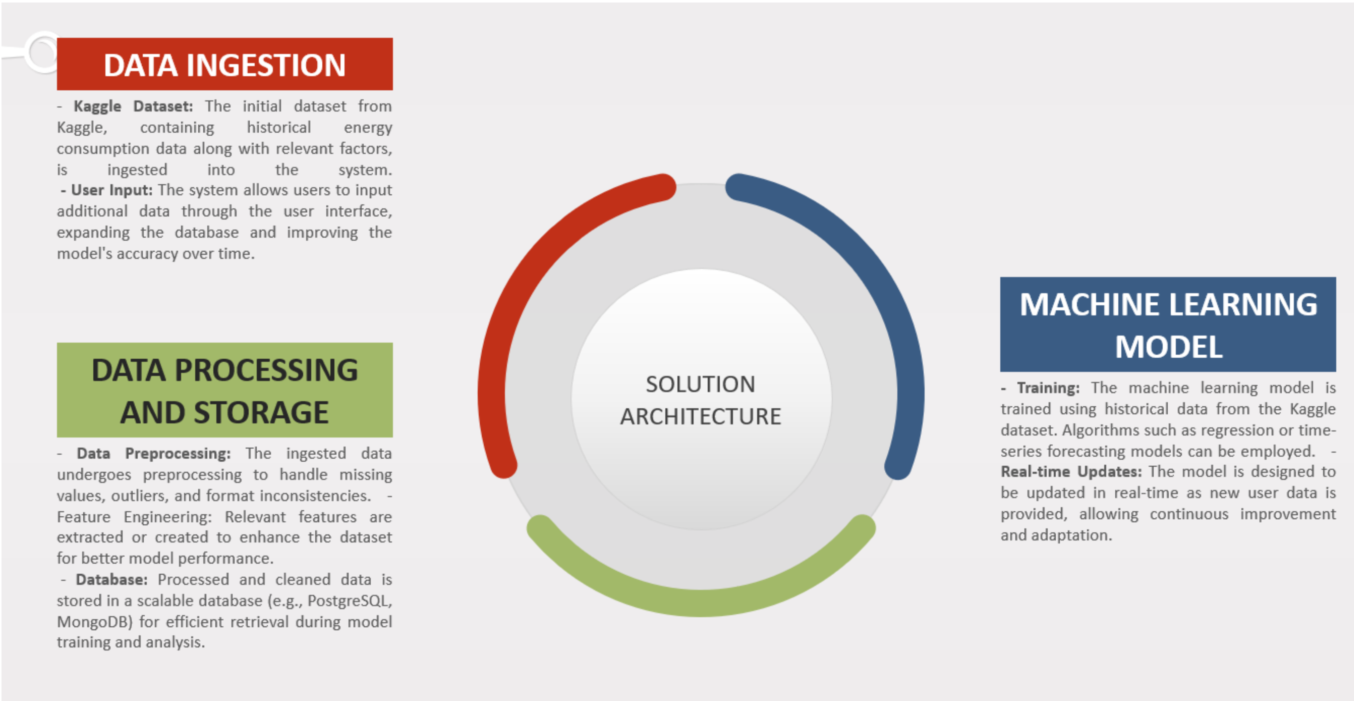
# PROJECT DESIGN

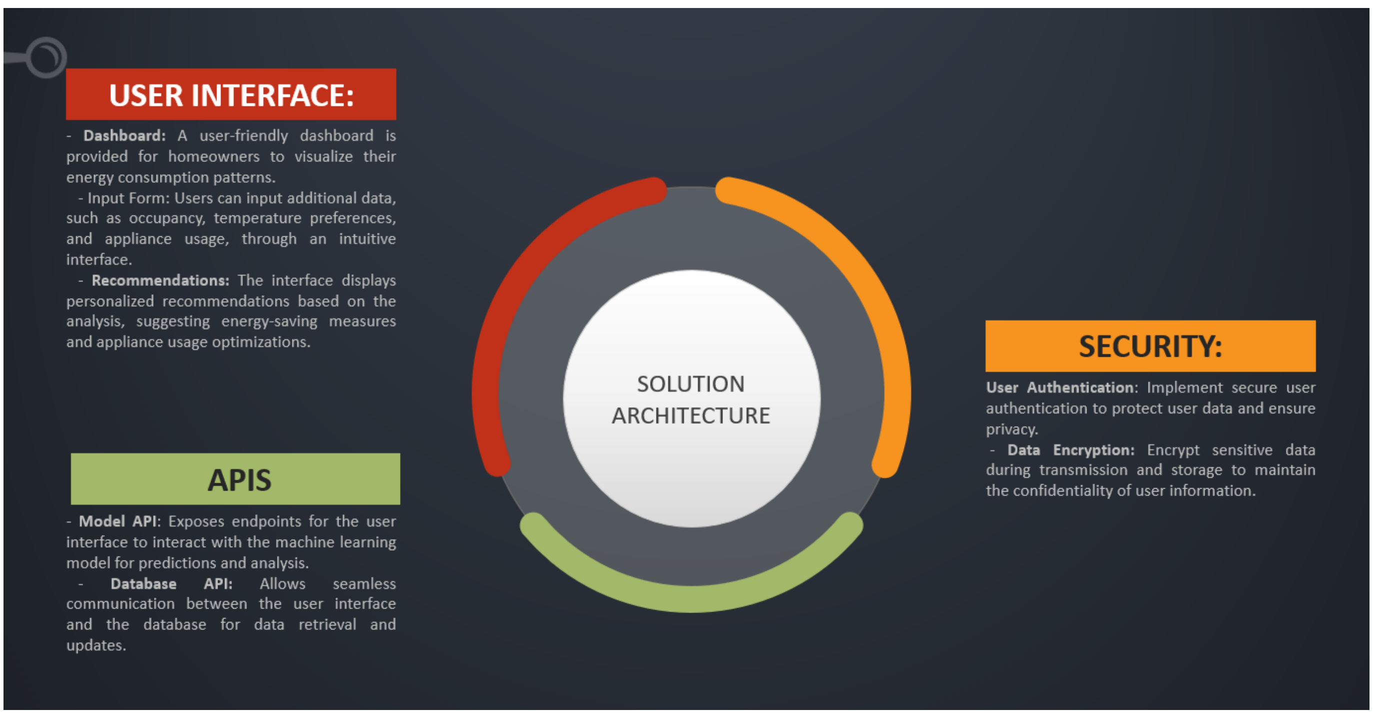
## Data Flow Diagram and User Stories



| Sprint | Functional Requirement (Epic) | User Story Number | User Story / Task | Story Points | Priority | Team Members |
|---|---|---|---|---|---|---|
| Sprint-1 | Import libraries and load data<br>Data preprocessing | USN-1 | This code section performs data cleaning and preprocessing, handling missing values, converting date and time to datetime format, extracting relevant features, applying one-hot encoding, creating a binary weekend flag, renaming columns, calculating total energy consumption, aggregating appliance data, setting 'datetime' as the index. | | Low | |
| Sprint-2 | Feature engineering and the target variable<br><br>Model training and evaluation<br><br>User input and prediction | USN-2 | Defines features and the target variable, splits data into train and test sets, trains a RandomForestRegressor model, and evaluates it using MSE, MAE, and R-squared. It then accepts user input, converts it to a DataFrame, performs one-hot encoding, predicts 'Global_active_power', and displays the prediction. | | High | |
| Sprint-3 | Appliance usage analysis | USN-3 | Use of a pie chart to show energy usage of distribution of appliances | | Medium | |
| Sprint-4 | Energy usage alert | USN-4 | Compares user appliance usage to average usage for the selected period | | Medium | |
| | | | Provides insights into appliance usage patterns | | | |
| Sprint-5 | Creation of dashboard | USN-5 | page banner was fixed at a width of 100% and height of 200px and the heading of RECSEA was used with font family Blockhead | | Medium | |
| Sprint-6 | Creation of an energy calculator | USN-6 | the description of the project was under a div element which makes it easy to use and edit | | High | |
| Sprint-7 | Frontend & backend integration | USN-7 | Using Flask | | High | |

## Solution Architecture



# PROJECT PLANNING & SCHEDULING

**Project Tracker, Velocity & Burndown Chart: (4 Marks)**

| Sprint | Total Story Points | Duration | Sprint Start Date | Sprint End Date (Planned) | Story Points Completed (as on Planned End Date) | Sprint Release Date (Actual) |
|---|---|---|---|---|---|---|
| Sprint-1 | 20 | 2 Days | 22 Oct 2023 | 23 Oct 2023 | 20 | 22 Oct 2023 |
| Sprint-2 | 20 | 6 Days | 24 Oct 2023 | 29 Oct 2023 | 17 | 30 Oct 2023 |
| Sprint-3 | 20 | 3 Days | 30 oct 2023 | 1 Nov 2023 | 20 | 31 Oct 2023 |
| Sprint-4 | 20 | 4 Days | 2 Nov 2023 | 5 Nov 2023 | 20 | 5 Nov 2023 |
| Sprint-5 | 20 | 2 Days | 6 Nov 2023 | 7 Nov 2023 | 15 | 9 Nov 2023 |
| Sprint-6 | 20 | 3 Days | 7 Nov 2023 | 9 Nov 2023 | 20 | 9 Nov 2023 |
| Sprint-7 | 20 | 4 Days | 14 Nov 2023 | 17 Nov 2023 | 20 | 17 Nov 2023 |

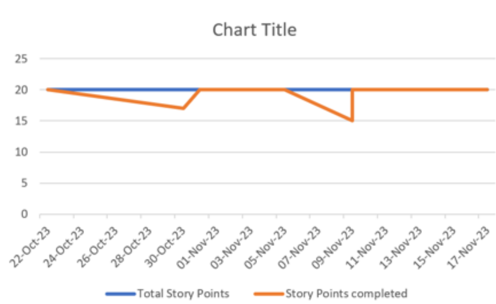
**Velocity:**

Imagine we have a 10-day sprint duration, and the team's velocity is 20 (points per sprint). Let's calculate the team's average velocity (AV) per iteration unit (story points per day)

$$AV = \frac{sprint\ duration}{velocity} = \frac{20}{10} = 2$$

Sprint 1: AV=20/2=10
Sprint 2: AV=20/6=3.33
Sprint 3: AV=20/3=6.66
Sprint 4: AV=20/4=5
Sprint 5: AV=20/2=10
Sprint 6: AV=20/3=6.66
Sprint 7: AV=20/4=5

**Burndown Chart:**



# CODING & SOLUTIONS

## Flask Integration

```python
from flask import Flask, render_template, request, redirect, url_for, session
import pickle
import pandas as pd
import matplotlib.pyplot as plt

app = Flask(__name__)
app.secret_key = 'm1n2b3v4c5x6z7'

# Load the model and dataset
data = pd.read_csv('processed_data.csv')
model = pickle.load(open('recaseamodel.pkl', 'rb'))

# Route for the home page
@app.route("/")
def index():
    return render_template("index.html")

# Route for the calculator page
@app.route("/calculate", methods=["GET", "POST"])
def calculator():
```

```python
# Route for the result page
@app.route("/result")

def show_result():
    predicted_power = session.get('predicted_power')
    power_status = session.get('power_status')
    normal_power = session.get('normal_power')
    plot_path = session.get('plot_path')
    return render_template("result.html", predicted_power=predicted_power, power_status=power_status,
                           normal_power=normal_power, plot_path=plot_path)

if __name__ == '__main__':
    app.run(debug=True)
```

### Result Page HTML Code

recasea1.py FlaskCalc.py calculator.html index.html result.html

```html
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <link rel="stylesheet" href="{{ url_for('static', filename='css/styles.css') }}">
  <title>Result - RECASEA</title>
</head>
<body>
  <div class="Banner">
  </div>
  <div class="ResultPage">
    <h2 >Result</h2>
    <div class="result-section">
      <h3>Predicted Global Active Power:</h3>
      <p>{{ predicted_power }}</p>
    </div>
    <div class="result-section">
      <h3>Power Status:</h3>
      <p>{{ power_status }}</p>
    </div>
    <div class="result-section">
      <h3>Normal Power:</h3>
      <p>{{ normal_power }}</p>
    </div>
    <div class="result-section">
      <h3>Energy Usage Distribution of Different Appliances:</h3>
      <img src="{{ plot_path }}" alt="Appliance Usage Distribution">
    </div>
  </div>
</body>
</html>
```

## Application

### Energy Consumption Calculator

Global Reactive Power (kW): 0.495

Voltage (V): 234

Global Intensity (A): 21

Kitchen Appliances Energy Sub-metering (W-hr): 1

Laundry Room Appliances Energy Sub-metering (W-hr): 2

Heating & Cooling Appliances Energy Sub-metering (W-hr): 17

Time of Day: 1 (Evening)

Weekday (0) or Weekend (1): 1

Other Appliances Energy Consumption (W-hr): 69.95

Predict

### Result

**Predicted Global Active Power:**

Predicted Global active power: 4.88 kW

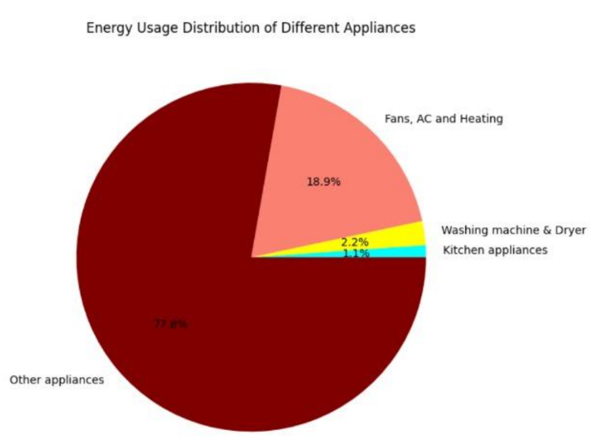
**Power Status:**

The predicted Global active power is higher than the regular usage for this time and weekend status.

**Normal Power:**

Normal value of Global active power for the specified time and weekend status: 1.74 kW

**Energy Usage Distribution of Different Appliances:**



**RECASEA Features**

1. Energy Consumption Prediction: Utilizes machine learning models to predict energy consumption based on various user-input parameters.
2. Usage Comparison: Compares predicted energy usage against normal patterns, providing insights into over- or under-utilization.
3. Appliance-specific Analysis: Allows users to analyze energy consumption for individual appliances for informed decision-making.
4. Personalized Recommendations: Offers tailored energy-saving suggestions to promote conscious consumption behavior.
5. Data Visualization: Generates visual representations like bar graphs or pie charts to depict appliance-wise energy usage.
6. Machine Learning Integration: Utilizes regression models to make accurate predictions based on historical data.
7. User Interface: Provides an intuitive and interactive web interface for seamless input and result interpretation.

**Web App Features**

1. User-friendly Interface: Offers an easy-to-navigate platform for users to input data and view predictions.
2. Result Visualization: Displays prediction outcomes, comparative analysis, and appliance-wise energy usage through graphs and charts.
3. Responsive Design: Ensures compatibility across devices, enabling users to access the app from various platforms.
4. Secure Authentication: Implements secure login mechanisms to protect user data and ensure privacy.
5. Real-time Prediction: Processes inputs instantly to generate predictions, delivering timely results to users.
6. Scalability: Designed to handle increased user load and accommodate potential expansions or updates in features.
7. Error Handling: Provides informative error messages to guide users in case of incorrect input or technical issues.

**Dataset Used:**

https://www.kaggle.com/datasets/uciml/electric-power-consumption-data-set

# PERFORMANCE TESTING

**Model used: Random Forest Regressor**

| S.No. | Parameter | Values |
|---|---|---|
| 1. | Metrics | **Regression Model:**<br>MAE -<br>MSE - 0.00045258<br>RMSE - 0.0063617<br>R2 score **-** 0.9997101 |
| 2. | Tune the Model | **Hyperparameter Tuning -**<br>max_depth= 15<br>n_estimators= 100<br>n_jobs= -1<br><br>**Validation Method -**<br>Cross Validation<br>Mean CV score: 0.00066788 |

## ADVANTAGES

1. Energy Efficiency Enhancement: RECASEA aids in identifying energy consumption patterns, promoting conscious usage and potentially reducing energy waste.
2. User Empowerment: Empowers users by providing insights into their energy usage, enabling informed decisions for conservation.
3. Cost Savings: Helps users potentially lower electricity bills by optimizing energy use based on predictive analysis.
4. Environmental Impact: Encourages eco-conscious behavior by reducing carbon footprint and contributing to sustainability efforts.
5. Data-Driven Insights: Utilizes data analytics to offer personalized recommendations for energy conservation.
6. Accessible Information: Provides accessible and visual representations of energy usage, aiding comprehension for all users.

### DISADVANTAGES

1. Data Accuracy Dependency: Accuracy of predictions relies heavily on the quality and relevance of historical data used in the model.
2. Limited Scope: Might face limitations in accurately predicting complex and fluctuating energy consumption patterns.
3. User Input Errors: Incorrect user input may lead to inaccurate predictions, potentially impacting the reliability of results.
4. Complexity for Users: Some users might find interpreting the analysis and implementing recommendations challenging.
5. Privacy Concerns: Collection of user data for analysis may raise privacy concerns; proper data handling is crucial.

## CONCLUSION

With its comprehensive system that helps users understand, optimise, and make informed decisions about their energy consumption, the RECASEA project is an outstanding instance of energy-conscious living. Through the application of predictive analysis and data-driven insights, it enables users to minimise waste, cut expenses, and support environmental sustainability. Its effectiveness is dependent on precise user input, up-to-date model updates, and reliable data. RECASEA, with its emphasis on mindful energy usage, represents a major step towards a sustainable future, despite possible drawbacks. Its influence, along with ongoing developments in user-centered design and data analytics, promises a revolutionary path towards effective and environmentally responsible energy management.

## FUTURE SCOPE

There are various possibilities for RECASEA to improve and grow in the future. Innovations in machine learning could improve predictive models and increase the precision of energy consumption estimates. Real-time data collection made possible by IoT device integration would provide consumers with quick insights into usage trends. By putting user feedback mechanisms in place, the system's algorithms can be improved and made to closely match the habits of specific users. Furthermore, the system might become more user-centric if it included tailored recommendations based on user behaviour and preferences.

Strong algorithmic development, ongoing data collection, and cooperation with energy-efficiency specialists are essential to achieving these improvements. To enhance its comprehensiveness, the platform could be expanded to support a wider variety of appliances and energy sources. Additionally, spending money on developing mobile apps and updating user interfaces can increase accessibility and user engagement, ensuring broader adoption and a more significant impact on energy-saving initiatives. These collective efforts would propel RECASEA into a more potent force in promoting sustainable energy practices.

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**Github source code link:**
https://github.com/smartinternz02/SI-GuidedProject-609524-1698083963/commit/eb5dab959b7a8b3f98ec47b71ec557a2270491bd

**Project demo link: https://youtu.be/dTF7n18P4xU**